Corporate Resiliency and the Choice between Financial and Operational Hedging*

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Abstract

We investigate how firms manage financial default risk (on debt obligations) and operational default risk (on delivery obligations). Financially constrained firms reduce operational hedging through inventory and supply chains in favor of cash holdings. Thus, firms' markup increases with financial default risk as they cut operational hedging costs. We show that the markup-credit risk relationship strengthens during adverse aggregate shocks, and markup reacted more strongly to credit risk for firms that became financially constrained, when their relationship lenders were shocked in 2008. This relationship, reflecting firms' strategic adjustments in operational hedging practices, is unexplained by managerial entrenchment and market power.

Keywords: financial default, operational default, resilience, liquidity, risk management, inventory, supply chains

JEL: G31, G32, G33

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1. Introduction

This paper examines how firms manage the dual risks of financial and operational default. Firms face contractual obligations on two fronts: financial debt contracts and operational contracts to deliver goods and services to customers. When adverse economic shocks occur, firms can face financial default on their debt obligations and operational default on their delivery commitment to customers as was the case during the COVID pandemic. Given constraints on internal cash flows and limited access to the capital market, firms must optimize their resource allocation to mitigate these two distinct default risks.

Our paper studies the tradeoff that the firm faces between allocating liquid resources to operational hedging, which would strengthen the firm's resiliency, and to the prevention of financial distress. Firms' operational hedging strategies include maintaining excess inventory, diversifying supply chains, and developing backup production capacity.[1] These strategies are costly, yet firms are willing to endure higher production costs to mitigate the risk of failure to deliver on their obligations to customers, which would impair their cash flow and impose a penalty on their reputation and franchise value. The firm's optimal balancing of these two hedging demands—financial hedging and operational hedging—provides a novel explanation for heterogeneity in operational resilience across firms. We find that financially distressed firms reduce operational hedging, particularly when external financing is costly. Thus, for firms with limited access to external capital, higher credit risk (or greater credit spread) leads to a higher price-cost spread or markup. This is because operational

[1] Operational hedging became prominent during the COVID pandemic and its aftermath, when corporate operational resilience was challenged by shocks that disrupted supply chains, depleted inventory, and impaired firms' ability to meet their delivery obligations.

hedging raises the firm's production costs and lowers the price-cost spread.[2]

We empirically test whether the firm's operational spread, measured by markup, (Sales− cost of goods sold)/sales, increases with the firm's credit risk, measured by Altman's Z-score (Altman, 1968, 2013a). A higher negative Z-score (-(*Z-score*)), which indicates greater credit risk, should raise the operational spread. We control for three measures of market power usually associated with markup, and for other characteristics. Our results support our hypothesis. We find that markup increases in -(Z-score) with a statistically and economically significant effect: an increase of one standard deviation in the firm's -(*Z-score*) raises the firm's markup by 7% relative to the sample average.[3] Furthermore, higher credit risk significantly lowers the cost of goods sold (CGS) after controlling for the firm's characteristics, supporting the model's prediction that credit risk affects markup through the lowering of operational hedging costs.

We test whether financial constraints amplify the positive relationship between markup and credit risk. To do so, we employ macroeconomic financial constraints and exogenous firm-specific shocks to credit supply. First, we find that during NBER-designated recessions, the positive markup-credit risk relationship is significantly stronger and the negative CGS-credit risk relationship is also stronger, suggesting that the positive markup–credit risk relationship is driven at least partly by costs.

We also test whether financial constraints amplify the positive relationship between markup and credit risk. To do so, we employ macroeconomic financial constraints and

[2]Notably, the effect of credit risk on operational spread stems primarily from lack of funds to spend on operational hedging, which is an investment in operational resiliency and differs from the debt overhang problem, which lowers investment (Myers, 1977).

[3]Our analysis thus introduces a new determinant of the firm's markup, while the market power variables are not found to predict higher markup.

exogenous firm-specific shocks to firms' financial constraints. First, we find that the positive markup-credit risk relationship is significantly stronger during NBER-designated recessions, when external financing is generally constrained. Notably, the negative CGS-credit risk relationship is also stronger during NBER recessions, suggesting that the positive markup–credit risk relationship is driven at least partly by costs.

Second, we test whether exogenous firm-specific shocks to credit supply during the 2008 subprime crisis lead financially constrained firms to exhibit a stronger positive relationship between markup and credit risk. We employ the data of Chodorow-Reich (2014) on banks that were impacted in September 2008 by the collapse of Lehman Brothers and generally by the mortgage-backed securities crisis, which forced them to cut loans. Firms with borrowing relationships with the impacted banks then became financially constrained. We find that for firms that were more exposed to these exogenous credit supply shocks, credit risk had a stronger positive effect on markup and a stronger negative effect on the CGS. Notably, we find no difference between the exposed and non-exposed groups during the pre-crisis period. Firms with higher credit risk that became exposed to lenders' shocks also reduced their operational hedging directly by lowering inventory holdings and, to a lesser extent, decreasing supply chain hedging.[4] Finally, we find that high–credit risk firms whose credit supply was shocked reduced their net leverage, suggesting that they employed the cash generated by lowering their operational hedging to lower their financial risk, as we propose. These tests alleviate concerns about the endogeneity of credit risk, as we study here the effect of the pre-crisis credit risk on the post-crisis outcomes for firms that became financially

[4]The effect on supply chain hedging is weaker because supply chain relationships involve long-term commitments and take time to adjust, unlike inventory that can adjust quickly.

constrained following a shock to their lenders.

We attend to alternative explanations for the positive effect of the firm's credit risk on its markup. The first is based on the disciplining role of debt for inefficient management, following Jensen (1986). By committing firms to payouts, debt forces managers to cut costs during adverse economic conditions. Since cost inefficiencies are more likely among entrenched managers who are shielded from mergers and acquisitions, we rank firms by the entrenchment indexes of Bebchuk, Cohen, and Ferrell (2009) and of Gompers, Ishii, and Metrick (2003). We divide firms into groups by whether they are among the top 30% ("high group") or bottom 30% ("low group") according to these entrenchment measures and estimate for each group the effects of -(*Z-score*) on markup and the CGS for firms that became financially constrained in the 2008 financial crisis when their lenders were shocked. The results do not show that our proposed effects of the Z-score on markup and CGS are stronger for firms with entrenched managers that need disciplining.

The second alternative explanation that we test is based on market power, following Chevalier and Scharfstein (1994) and Gilchrist et al. (2017). These authors propose that firms with market power that become liquidity-constrained can raise their prices and markups and consequently their cash flows. Thus, they can meet their short-term liquidity needs even if it hurts their market share and long-term profitability. Notably, our analyses include variables that control for market power, and our finding of the negative effect of $-(\textit{Z-score})$ on the CGS supports our proposal that markups on financially constrained firms rise through the lowering of operational hedging costs. Nevertheless, we directly test the market power–based explanation of the positive markup–credit risk relationship by estimating our models separately for firms with high market power—those among the top 5% of their industry sellers, which are likely to have market power—and the remaining firms. Our findings do not support the market power–based explanation. The positive markup–credit risk relationship is stronger among firms with low rather than high market power. This finding also holds in the contexts of the NBER recessions and the 2008 funding shocks to lending banks. That is, even in times of acute liquidity shortages, the positive markup–credit risk relationship is not associated with higher market power.

A third explanation for our proposed effects of –(*Z-score*) on markup and CGS is due to Maksimovic and Titman (1991). They show that firms may have incentives to lower product quality and marginal cost when they are near financial distress because consumers do not find out about product quality in the short term.[5] This follows Myers (1977) suggestion that debt overhang inhibits investments that create value in the long term because existing creditors act like a tax, distorting real investment decisions. Myers rationale also applies to our case of investment in operational hedging. These are not mutually exclusive cases; managers could lower both product quality and operational hedging in response to the threat of default. We attend to this explanation by testing whether markups adjust downward in the long term, presumably after most consumers discover that product quality has been lowered. We find no evidence of long-term declines in markup.

Finally, we examine whether avoiding financial default becomes a dominant consideration for firms' valuation. High credit risk may lead to financial default before any operational default such that operational hedging does not help. Testing this prediction using stock returns during the COVID era (2020–2021), we expect that pre-COVID operational hedging choices matter less for the value of firms that entered the COVID era with an already high

[5]Phillips and Sertsios (2013) test this idea in the airline industry and find broadly consistent evidence.

credit risk. We find supportive results. Investing in operational hedging raises firms' value (by preserving their franchise value) following adverse operational shocks only in firms whose credit risk was initially low.

In summary, our novelty is in proposing that firms need to hedge not only against defaults on their financial contracts (their debt obligations) but also against defaults on their operational contracts (their commitment to deliver products to customers). Because both forms of hedging impose demands on the firms' limited resources, financially constrained firms face a tradeoff in allocating those resources to protect against these dual default risks.

1.1 Related Literature

Our paper is related to studies of the real effects of financing frictions that show that these frictions can affect investment decisions and employment.[6] A general theme in these studies is that financial constraints induce firms to focus on short-term actions that boost liquidity, even when they reduce long-term value. For example, Rampini and Viswanathan (2010) argue that constrained firms may be forced to reduce risk management when long-term benefits are high because of short-term financial constraints. The tradeoff between operational and financial hedging that we propose is related to this key idea. Firms reduce value-enhancing operational hedging to save cash and protect themselves against financial distress. Our contribution to this literature is to focus on operational hedging, which had not been examined before, and in the quantification of the tradeoff between hedging against financial risk and

[6] See Lemmon and Roberts (2010); Duchin, Ozbas, and Sensoy (2010); Almeida et al. (2012); Giroud and Mueller (2016); see Stein (2003) for a review. There are also studies of the effect of financial constraints and financial distress on financial policies such as cash, credit lines, and risk management; see Almeida, Campello, and Weisbach (2004); Sufi (2009); Bolton, Chen, and Wang (2011); Acharya, Davydenko, and Strebulaev (2012).

operational risk. Whereas other studies focus on firms' policies intended to avoid financial default, we propose that firms are subject to two types of costly default that they need to manage: the commonly analyzed default on financial obligations and our proposed operational default, that is, the failure to fulfill contractual obligations on delivering output to customers. Our analysis as well as those mentioned about are all related to Myers (1977) debt overhang problem which suggests that equity holders of levered firms under-invest in positive NPV projects when the benefits accrue partly to creditors, a mechanism that extends naturally to the operational hedging decisions we study.

Our paper also relates to that of Froot, Scharfstein, and Stein (1993), who propose that corporate hedging against cash shortfalls helps the firm mitigate the risk of not being able to finance valuable investment opportunities. Gamba and Triantis (2014) study firms' risk management policies to avoid financial distress that are carried out by holding liquid assets and financial derivatives and maintaining operational flexibility. In our analysis, operational hedging is not a means to avoid financing shortfall but, rather, a way to compete with financial hedging. Hedging against cash shortfalls that raise financial default risk reduces the funds available for operational hedging when firms face financial constraints, thus increasing the probability of default on the delivery of contractual obligations. In our setting, financial hedging and operational hedging are substitutes.

2. Hypothesis Development

We focus on two types of default risk that compete for firms' limited financial resources: financial default on debt obligations and operational default on customer delivery commitments.

Consider a firm with existing debt obligations and customer contracts that promise the delivery of merchandise. The firm operates in an uncertain environment where economic shocks can threaten both its ability to service debt because of cash shortage and its capacity to fulfill customer orders because of shock to production (e.g., a disruption to its supply chains). Financial default will eliminate shareholder equity, while defaulting on delivery obligations will lower firm value due to a loss in the firm's franchise value (loss of future orders). The firm needs to decide whether it should preserve cash to ensure debt repayment or invest its cash in operational resilience to guarantee customer deliveries.

The answer depends on whether the firm can meet its debt obligations while maintaining operational capabilities. Operational hedging encompasses costly strategies that help firms meet delivery obligations during adverse conditions. These strategies include producing extra output quantity and maintaining it as inventory beyond normal operating needs, diversifying supply chains across multiple suppliers and regions, and investing in backup production capacity. While these investments reduce the risk of operational default, they require significant upfront expenditures that reduce available cash.

Financial default destroys all future value, including potential revenues from customer contracts and franchise value. Thus, any investment in operational hedging—no matter how valuable for ensuring customer deliveries—becomes worthless if the firm cannot service its debt. When credit risk is high enough, the threat of financial default thus takes precedence over operational concerns. Firms cut or eliminate operational hedging to save cash for debt repayment. As credit risk declines, the firm can shift more resources into operational hedging, managing the balance between financial hedging and operational hedging.

The extent of operational hedging is reflected in its cost, which appears directly in the firm's cost structure. Producing extra output for inventory and paying its carrying costs, diversifying supply chains that require managing relationships with multiple vendors, and maintaining excess capacity are all reflected in higher costs. These costs flow through to the firm's production cost, reducing profit margins. This logic leads to our first hypothesis.

Hypothesis 1: Firms with higher credit risk will exhibit higher markups and a lower cost of goods sold.

Notably, the mechanism behind Hypothesis 1 is purely cost based: by cutting operational hedging, firms lower costs, thus increasing markups even in competitive markets where firms are price takers and output prices are given. Traditional explanations link higher markups under financial distress to firms' ability to raise prices (Gilchrist et al., 2017). In contrast, our mechanism does not require pricing power: even price-taking firms can widen their markups when credit risk rises by trimming costly operational hedges, thereby lowering marginal costs while leaving prices unchanged. We follow this intuition in our empirical work to distinguish our story from the traditional ones.[7]

2.1 Role of Financial Constraints

The tradeoff between financial and operational hedging intensifies when firms face constraints on external financing. Firms can bridge temporary cash shortfalls by accessing capital markets or credit lines. They can borrow while pledging their future cash flows obtained from sales. However, when external financing becomes costly or unavailable and the pledgeability of future cash flows is limited, the competition for internal resources becomes more severe. This reasoning leads to our second hypothesis.

[7] A formal model that supports this intuition is available in an Internet Appendix.

Hypothesis 2: The positive relationship between credit risk and markup will be stronger for financially constrained firms.

In summary, the core insight is that financial and operational hedging compete for scarce firm resources, with financial hedging taking priority when credit risk is high due to the sequential nature of financial and operational obligations. Under this framework, higher credit risk raises markups and lowers costs, effects that intensify when external financing is harder to obtain.

3. Empirical Analysis

We now test the two hypotheses on the link between operational hedging and credit risk. First, greater credit risk or probability of default lowers operational hedging, indicated by an increase in the price-to-unit cost difference, or the firm's markup. Second, the positive relationship between markup and credit risk is stronger for firms that are financially constrained, indicated in our model as having a lower pledgeability of future cash flows.[8]

We measure operational hedging by $Markup = (Sales - CGS)/Sales$, where CGS is the cost of goods sold (CGS). Increased spending on operational hedging lowers *Markup*. Operational hedging is partly accomplished by hoarding inventory and by broadening supply chains that includes expanding and diversifying the number of suppliers with whom

[8]To anchor our empirical tests, we develop in the Internet Appendix a model of a competitive (price-taking) levered firm's optimal operational hedging policy when facing two types of costly default: financial default (on debt service) and operational default (on customer contracts). We build on the financial hedging framework of Acharya, Davydenko, and Strebulaev (2012) by incorporating operational hedging, where (i) financial hedging takes the form of cash savings to prevent default on debt that matures before customer contract settlement dates, and (ii) operational hedging takes the form of excess inventory in the benchmark model and supply chain diversification in an extension. Operational hedging incurs a marginal cost that is increasing in the extent of hedging, and financial hedging incurs a potential cost in that it crowds out investment in operational hedging.

the firm works.[9]

We begin by validating that our proposed measures of operational hedging—inventory and supply chain breadth—are consistent with our model mechanics, where operational hedging mitigates the effects of shocks to firms' output and sales for price-taking firms. We test whether higher inventory and greater supply chain breadth mitigate the sales decline during economic shocks measured by NBER-designated recessions. In addition, we test whether $Markup$, our measure of operational spread, declines with inventory and supply chain breadth.

We then test the two major hypotheses in Section 2. First, we test whether $Markup$ increases in the firm's credit risk measured by the negative value of Altman's (1968) Z-score, which indicates a greater likelihood of default and positively affects credit spreads. We also test if CGS declines in credit risk. Second and more importantly, we use financing shocks to test whether tighter financial constraints or lower pledgeability strengthen the positive relationship between $Markup$ and credit risk. The first test examines the relationship between $Markup$ and -(*Z-score*) during NBER recession periods, when capital markets are depressed and financing is scarce. The second test employs the shocks to firms' lenders during the subprime mortgage crisis of 2008, which curtailed their ability to provide credit to their relationship borrowers, following the analysis by Chodorow-Reich (2014). We test whether the $Markup$ (and CGS of exposed firms—those whose lenders were more strongly hit by the crises—exhibited a stronger relationship with their -(*Z-score*) measured before the crisis. We conclude by testing whether the effect of financing distress on markups

[9]Operational hedging may encompass other measures; inventory and supply chain diversification may, however, be the most salient and easily measured.

operates through market power, which enables firms to raise prices. By our proposed mechanism, markup rises in response to financial distress because firms lower their operational hedging costs.

3.1 Data and Empirical Definitions

We employ quarterly data from 1971 to April 2020, a span of 197 quarters, from Compustat. We exclude firms in financial industries (SIC codes 6000-6999) and utility industries (SIC codes 4900-4949), and firm-quarters involved in major mergers (Compustat footnote code AB). We include firm-quarter observations with market capitalization greater than $10 million and quarterly sales above $1 million at the beginning of the quarter, inflation adjusted to the end of 2019. Our sample includes 18,338 firms with an average asset value of $2.7 billion and a median of $0.30 billion (inflation adjusted to the end of 2019). Altogether we have 573, 041 firm-quarters.

3.1.1 Variable Definitions

Operational spread is measured by $Markup$, defined as sales ($SALEQ$) minus cost of goods sold ($COGSQ$) divided by sales. The variable $Markup$, the price-unit cost spread, proxies for our model's operational spread, which is modeled as the spread between price and the marginal cost of output production.[10] Our second dependent variable is CGS, defined as the CGS ($COGSQ$) scaled by assets (ATQ), which increases with operational hedging costs.

Our key explanatory variable is the firm's credit risk proxied by the negative value of

[10] See Internet Appendix for details.

Altman's (1968) Z-score.[11] Das, Hanouna, and Sarin (2009) find that the yield spread on corporate debt is decreasing in the Z-score. The model includes variables that control for the firm's investment and its debt capacity: total assets, in logarithmic form, which account for the firm's size; Tobin's Q, which accounts for the firm's growth prospects, calculated as the sum of common shares outstanding ($CHOQ$) multiplied by the stock price at the close of the fiscal quarter ($PRCCQ$), preferred stock value ($PSTKQ$) plus dividends on preferred stock ($DVPQ$), and liabilities (LTQ) scaled by total assets (e.g., Covas and Den Haan, 2011). The inclusion of Tobin's Q controls for shocks to valuation and growth opportunities that might disproportionately affect firms with higher credit risk, potentially influencing their operational decisions and hedging decisions. Other control variables are cash holdings ($CHEQ$), cash flow (IBQ+DPQ), and tangible assets ($PPENTQ$), all scaled by total assets. The models with $CGS/assets$ as the dependent variable include the contemporaneous sales–assets ratio because the CGS is partly and mechanically related to current sales. We also control for market power, which affects the firm's markup (Lerner, 1934) and inventory behavior (Amihud and Medenelson, 1989), using a dummy variable that equals one if the firm ranks among the top four sellers in the industry in a given quarter (zero otherwise), and the firm's $Sales/industry\ sales$. The models include firm fixed effects and industry–quarter fixed effects, using Fama and French's 48 industries, which also controls for changes in the concentration of the industry to which the firm belongs.

Operational hedging is indicated by inventory and by supply chain breadth.[12] Inventory

[11] Since $EBIT$ is not available in Compustat quarterly data, we use $OIBDP$ instead in our calculation of the Z-score (Chen et al., 2017).

[12] The 2020 COVID pandemic highlighted the importance of inventory—which in many cases was impossible to replenish at reasonable cost or in a timely manner—and of supply chain diversification to circumvent shutdowns of some manufacturing facilities.

($INVTQ$) scaled by sales proxies for excess production. The supply chain hedging variable is created using information from the Factset Revere Supply Chain Relationships database on firms' suppliers, which contains comprehensive relationship-level data between firms, starting from April 2003.[13] The FactSet database notes the relationship between two firms with information about the identities of the related parties, the start and end date of the relationship, the type of relationship (e.g., competitor, supplier, customer, partner, etc.), and the firms' geographic origins. We aggregate the relationship-level data to the firm–quarter level and calculate three measures of supply chain hedging for each firm in each quarter: (i) ln(1 + number of suppliers); (ii) ln(1 + number of supplier regions), where supplier regions are country and state/province combination; (iii) ln(1+number of out-of-region suppliers), that is, not from the firm's region. We merge the supply chain data with our main sample, yielding a total of $151,985$ firm–quarter observations covering $6,204$ firms from mid-2003 to the first quarter of 2020. The median firm has four suppliers from three regions in a given quarter, of which three suppliers are not from the firm's region. The supply chain hedging index, SCH, is the first principal component from the principal component analysis of the three individual measures over the whole panel, which explains 97% of the sample variance. The three measures (i) through (iii) have similar weights of 0.575, 0.580 and 0.578, respectively. A higher value of SCH indicates greater supply chain breadth and more intensive hedging along the supply chain.

Table 1 presents summary statistics of the variables in our study. All continuous variables in our analysis are winsorized at 1% and 99%.

[13] FactSet Revere's coverage of supply chain information is much better than Compustat's segment data and used by some supply chain studies (e.g., Ding et al., 2020).

[INSERT Table 1.]

3.2 Hedging Operational Risk through Supply Chain and Inventory

Operational hedging encompasses strategies such as building up extra inventory or diversifying supply chains across multiple suppliers and regions. More generally, it reflects spending on slack and excess capacity that enables firms to produce the requisite output in case of operational stress. While these investments increase costs, they enable firms to deliver on their contract obligations and maintain higher sales when adverse economic shocks disrupt normal operations.

To validate that our empirical measures capture operational hedging activities, we first test whether firms with higher levels of inventory and supply chain diversification prior to NBER-designated recessions experience smaller declines in sales during those recessions. For each recession period, we estimate a separate cross-sectional regression with the dependent variable being $\Delta(Sales/assets)$, the change in the average level of firm sales (scaled by total assets) between the recession quarters and the average eight-quarter period before the recession. Because a recession may have warning signs that affect the firms' operational hedging before its onset, we use the inventory and supply chain hedging data ending four quarters before the onset of each recession. The control variables are fixed as of the latest quarter before the onset of the recession. In these regressions, we exclude firm–quarters with zero inventory.[14] The model includes industry fixed effects, and standard errors are clustered at the industry level.

[INSERT Table 2.]

[14] The results are qualitatively similar when these observations are included.

Table 2 presents the results. Higher levels of inventory and supply chain hedging before the recession mitigate the decline in sales during the recession compared with average sales during the eight pre-recession quarters. Naturally, sales declined during the recessions,[15] but less so for firms with higher inventory and supply chain breadth before the recession. The coefficients of the pre-recessions' $Inventory/sales$ are all positive and significant, averaging 0.02 across the six recessions. For SCH, the coefficient is also positive and significant.[16] Overall, we find that firms with higher levels of operational hedging suffer less severe disruptions in output deliveries when recession shocks hit.

3.3 Markup, the CGS and Operational Hedging

We propose that operational spread declines when the firm increases spending on operational hedging. We now test whether $Markup$, our empirical measure of the operational spread, declines in inventory and supply chain breadth, our empirical measures of operational hedging. We estimate the following model using quarterly data:

$$\begin{aligned} Markup_{j,t} &= \beta_1 * Invt/sales_{j,t-1} + \beta_2 * SCH_{j,t-1} + Control\ variables_{j,t-1} \\ &\quad + \text{Firm Fixed Effect (FE)} + \text{Industry}*\text{Year–Qtr FE} \end{aligned} \tag{3.1}$$

We expect $\beta_1 < 0$ and $\beta_2 < 0$. We also estimate the model with the dependent variable being $CGS/assets_{j,t}$, expecting $\beta_1 > 0$ and $\beta_2 > 0$.

[INSERT Table 3.]

[15] The average sales–assets ratio is 0.012 lower during the recessions, compared with the previous eight-quarter periods. The average decline in the sales–assets ratio ranges from −0.023 to 0.007, across the six recessions in our sample. Apart from the first recession (1973Q4–1975Q1), all recessions witness an average decline in the sales–assets ratio.

[16] Data for SCH are available only for the recession of 2007Q4–2009Q2.

In Table 3 we find that that markup and the CGS are both affected by the two variables that indicate operational hedging. Higher values of inventory and supply chain hedging, which raise the firm's unit cost, significantly lower markup and raise CGS. To illustrate the economic significance of the estimated effect, the estimation in column 1 implies that one standard deviation increase in SCH lowers markup by 0.01 and one standard deviation increase in $Inventory/sales$ lowers markup by 0.04. These values are sizable relative to the mean $Markup$, which is 0.317. After controlling for firms' market power variables and industry–quarter fixed effects (column 2), the estimated effect of SCH is 0.007 while that of $Inventory/sales$ remains the same. Notably, the coefficients of the two market power variables included in column 2, the *Top4industryseller* dummy variable and the firm's *Sales/industry sales*, are 0.0056 and -0.57, respectively, with standard errors of 0.0040 and 0.13. Thus, there is no evidence that market power drives up the markup. Overall, the results suggest that markup and the CGS reflect in part the effects of the firm's operational hedging activity.[17]

3.4 Baseline Results

Hypothesis 1 states that firms closer to financial distress reduce spending on operational hedging, resulting in a higher operational spread, which we proxy by *Markup*, and lower costs, which we measure by $CGS/assets$. We estimate the following model:

$$Y_{j,t} = \beta_1 * -(Z-score)_{j,t-1} + Control\ variables_{j,t-1} + \text{Firm FE} + \text{Industry}*\text{Year–Qtr FE} \quad (3.2)$$

[17]These regressions exclude firm–quarters with zero inventory. The results are qualitatively similar when these observations are included.

$Y_{j,t}$ is either $Markup_{j,t}$ or $CGS/assets_{j,t}$ and -(*Z-score*), which is lagged, increases in the firm's credit risk, which implies a higher default spread. By our hypothesis, -(*Z-score*) has a positive effect on $Markup$ and a negative effect on $CGS/assets$. The model includes the control variables used earlier as well as firm and industry–quarter fixed effects, with standard errors clustered by firm and by year-quarter.

[INSERT Table 4.]

Table 4 presents our baseline results. The operational spread measured by $Markup$ is positively affected by the firm's credit risk, measured by -(*Z-score*). A higher likelihood of financial default and a greater need for liquidity to hedge financial risk make firms reduce spending on operational hedging. Then unit cost declines and markup increases. The economic meaning of the estimated effects is seen in column 1, where an increase of one standard deviation in -(*Z-score*) raises the firm's markup by 7% relative to its average markup value, or by 5% relative to its average after controlling for market power and industry–quarter fixed effects. In columns 3 and 4 we find that the CGS declines in the firm's credit risk. An increase of one standard deviation in -(*Z-score*) lowers $CGS/assets$ by 2% relative to the average $CGS/assets$, with an almost similar effect after controlling for market power variables and industry–quarter fixed effects. The market power variables' effects are nonsignificant.[18] Our findings are consistent with our prediction that the need to avoid financial default induces firms to shift funds away from operation hedging to support financial resilience.

[18]The coefficients of the two market power variables included in column 2, the *Top 4 industry seller* dummy variable and the firm's *Sales/industry sales*, are −0.00019 and −0.28 with standard errors of 0.0047 and 0.078, respectively.

3.5 Effect of Financial Constraint

Our model predicts that lower pledgeability of the firm's future cash flows leads to a stronger positive markup–credit risk relationship. (In our model in the Internet Appendix, lower pledgeability is represented by a lower τ.) A firm facing lower pledgeability is more likely to be financially constrained. The research question is whether financial constraint strengthens the positive relationship between markup and credit risk. Because financial constraints are endogenously related to the firm's performance, we employ two exogenously imposed shocks to financial constraints in our tests: economic recessions and the 2008 financial crisis. In the first test we examine the effect of a systematic increase in financial constraint, while in the second test we examine the effect of firm-specific increases in financial constraints on the relationship between credit risk and both markup and the CGS. By our model, these relations should be strengthened because, when constrained, firms must shift resources from operational hedging to hedge against financial default.

3.5.1 Recession Periods

Liquidity is scarce during economic recessions, making it harder for firms to raise capital upon demand when they need it to service their financial obligations. We test whether credit risk has a stronger effect on markups during recessions, as our model predicts would be the case when pledgeability is low, making firms financially constrained. Our test augments the baseline model in Table 4 of the effect of -(*Z-score*) on markup and the CGS by adding an interaction term -(*Z-score*)×*Recession*, where *Recession* is a dummy variable that equals one during the NBER-designated recession quarters and zero otherwise. The values of

-(*Z-score*) and of the firm control variables are fixed for the duration of the recession periods at their level at the most recent quarter before the start of each recession, because the Z-score may be affected by the recession.[19]

The results, presented in Table 5, suggest that during recessions, firms with higher credit risk—a higher -(*Z-score*)—before the onset of a recession reduce their operational hedging by more, reflected in a greater increase in their markup and a greater decline in their CGS. The interaction term -(*Z-score*)×*Recession* has positive and significant coefficients in the markup regressions, columns 1 and 2, and negative and significant coefficients in the CGS regressions, columns 3 and 4. These results support our model's prediction that, when faced with financial constraint, firms are more aggressive in shifting liquidity from operational hedging to financial hedging, thus lowering their unit costs and raising their markup.

[INSERT Table 5.]

3.5.2 Credit Supply Shocks in 2008

The second test of the effects of financing constraints on the markup–credit risk relationship employs the firm-specific exposure of firms to the credit shock due to the 2008 financial crisis. During this crisis, especially starting in October 2008, a number of banks could no longer extend credit to firms with which they had lending relationships. We test whether firms whose lenders were adversely affected by the 2008 crisis, which we call exposed firms, exhibit a stronger effect of -(*Z-score*), which is positive for *Markup* and negative for $CGS/assets$.

[19] See the recommendation, for instance, of Roberts and Whited (2013) on the issue of studying the effects of shocks on the dependent variables.

By our model, exposed firms with higher credit risk should have shifted resources when becoming financially constrained from spending on operational hedging to liquidity that helps avoid financial default, thus lowering their costs and raising their markup.

We employ three measures of the adverse impact of the 2008 crisis on lenders' ability to provide credit, proposed by Chodorow-Reich (2014):[20] (i) % Loans reduction, the number of loans that the firm's lenders extended to all firms (excluding the firm in question) in the nine-month period from October 2008 to June 2009, relative to the average of the 18-month period from October 2005 to June 2006 and October 2006 to June 2007; (ii) Lehman exposure, that is, exposure to Lehman Brothers through the fraction of a bank's syndication portfolio where Lehman Brothers had a lead role; and (iii) ABX exposure, namely, the extent of banks' exposure to toxic mortgage-backed securities, calculated using the correlation between banks' daily stock returns and the return on the ABX AAA 2006-H1 index.

The relationship between our sample firms and bank lenders is calculated using data from the LPC DealScan database. For each firm and each of the three measures, we calculate a weighted average of the measure over all members of the last pre-crisis loan syndicate of the firm, where the weight is the lender's share in the firm's last pre-crisis loan syndicate. The detailed construction of the three variables at the firm level is provided by Chodorow-Reich (2014). We construct the three variables such that a larger value implies greater exposure to the financial crisis through the firm's lenders. Our sample here is restricted to the $2,429$ firms in Chodorow-Reich (2014) database.

Table A.2 in the Appendix presents the pre-financial crisis characteristics of firms that are sorted into quartiles (Q1–Q4) based on their exposure to the 2008 financial crisis for

[20] We thank Chodorow-Reich for sharing his data with us.

the three measures of exposure. For each characteristic, the table reports the mean values across all quartiles and compares firms in the highest and lowest exposure quartiles (Q4 versus Q1). We observe that firms with higher exposure are larger and possess greater market power and have lower credit risk (lower -(*Z-score*)) and lower cash holdings according to some exposure measures. We account for these pre-crisis differences by including the pre-financial crisis characteristics (and their interactions with a post-crisis indicator) in our empirical model (3.3).

We estimate the effect of the exposure to shocked lenders on the relationship between credit risk, markup, and the CGS using the following model:

$$\begin{aligned} Y_{j,k,t} = \alpha &+ \beta_1 * \text{-}(\textit{Z-score})_{j,2007} \times \textit{Lender exposure}_{j,t} + \beta_2 * \textit{Lender exposure}_{j,t} \\ &+ \sum_m \beta_{3,m} * \textit{Control variable}_{m,j,t-1} \\ &+ \sum_m \beta_{4,m} * \textit{Control variable}_{m,j,t-1} \times \textit{Lender exposure}_{j,t} + \theta_j + \eta_{k,t} + \epsilon_{j,t} \ . \end{aligned} \quad (3.3)$$

$Y_{j,k,t}$ denotes $Markup$, $CGS/assets$, $Inventory/sales$, SCH, or $Net\ leverage$ for firm j in industry k in quarter t. The periods studies are the two pre-crisis years, January 2006 to December 2007, and the two post-crisis years, January 2009 to December 2010, skipping the crisis year, 2008. Notably, -$(\textit{Z-score})_{j,2007}$ is fixed before the crisis at the end of 2007. Lender exposure equals zero for the pre-crisis period and the respective value for the post-crisis period. The control variables are the same as in the baseline regression (Table 4), being fixed at the end of 2007 for the post-crisis period, and the model includes their interaction with the lender exposure variables. The model includes firm fixed effects and industry–quarter fixed effects, with standard errors clustered at the firm level.

Panel A of Table 6 presents the results for markup and the CGS. Consistent with our proposition, the coefficient β_1 of -$(Z\text{-}score)_{j,2007}$$\times$$Lender\ exposure_{j,t}$ is positive and significant for the markup model (even-numbered columns) and negative and significant for the CGS model (odd-numbered columns). These results are consistent for all three lender exposure variables. Markup increased for firms with higher credit risk whose lenders were more adversely affected by the financial crisis, making them financially constrained. These firms reduced spending on operational hedging, as evident from the significant lowering of $CGS/assets$ which implies shifting resources to avoid financial default. Gauging the economic significance of the joint impacts of the firm's credit risk and its exposure to financial crisis, using column 1 as an example, we find that a one unit higher value of the firm's -(*Z-score*) and a reduction of the number of loans by its lender to other borrowers by 10% during the financial crisis led to a 0.011 wider markup. This constitutes 3% of the average markup in the pre-crisis period. Column 3 shows that a one unit higher value of -(*Z-score*) and a 10% exposure of lender to Lehman led to markup widening by 0.019, which is 5% of the pre-crisis average markup.

Panel B of Table 6 examines the impact on inventory holdings and supply chain hedging (SCH) of exposure to shocked lenders for high-credit risk firms. The coefficient β_1 is negative and significant for inventory across all three lender exposure measures (columns 1, 3, and 5), indicating that firms with higher credit risk whose lenders were shocked by the financial crisis reduced their inventory holdings, which suggests they lowered their operational hedging. The results for supply chain hedging (SCH) show a similar pattern with negative coefficients across all specifications, with statistical significance primarily for the ABX exposure measure (column 6). These findings provide direct evidence that firms with high credit risk that became financially constrained scaled back their operational hedging activities. To gauge economic significance using column 1, a one unit higher value of -(*Z-score*) combined with a 10% reduction in loans by the firm's lenders during the crisis led to a decrease of 0.017 in the inventory-to-sales ratio. For supply chain hedging in column 6, a one unit higher -(*Z-score*) and 10% ABX exposure resulted in a reduction of 0.055 in the supply chain hedging index.

In Panel C we examine firms' use of the gains from reducing the cost of operational hedging. The dependent variable in the panel is Net leverage, the firm's debt minus cash scaled by total assets. The coefficients of -(*Z-score*)×*Lender exposure* is significantly negative across all three crisis exposure measures, suggesting that high-credit risk firms whose lenders were more strongly shocked in the 2008 crisis reduced their net leverage significantly more than other firms. These findings directly address the mechanism underlying our main results: financially vulnerable firms exposed to exogenous credit shocks cut operational hedging, widen their profit margins, and deploy the freed up cash flow to strengthen their financial resilience by reducing net leverage. This finding is consistent with our hypothesis: when external financing is constrained, firms with high credit risk prioritize financial hedging over operational hedging, reallocating scarce liquidity toward improving their ability to meet debt obligations and avoid financial default.

[INSERT Table 6.]

In the remainder of this subsection, we study the dynamic effects of the interaction term $\beta_1 *$-$(\textit{Z-score})_{j,2007} \times \textit{Lender exposure}_{j,t}$ before and after the crisis. We replace the lender exposure variable in equation (3.3) with an interaction terms $\beta_n *$-$(\textit{Z-score})_{j,2007} \times (LE, D_n)$

where (LE, D_n) is the actual value of lender exposure for quarter n and zero otherwise, and n equals $-4, \ldots, -1, 1, \ldots, 4, \{+5, +8\}$, with $\{+5, +8\}$ capturing quarters +5 to +8. This numbering applies to the last four quarters in the pre-crisis period, Q1–Q4/2007, the four post-crisis quarters, Q1-Q4/2009, and $D_{\{+5,+8\}} = 1$ applies to quarters Q1–Q4/2010. We expect the coefficients β_n to be nonsignificant in the pre-crisis period, $n = -4, \ldots, -1$, and to be significantly positive for the post-crisis period.

Table 7 presents the results. In all columns, the coefficients β_n are mostly significant after the crisis, starting from $n = +2$, while being nonsignificant before the crisis for $n < 0$. At the bottom of each column, we present the results of an F-test of the joint significance of all the coefficients β_n in two groupsf, the four quarters before the crisis and the four quarters after it. In all tests, the F-value shows that the coefficients β_n for the post-crisis four quarters are statistically significant and the coefficients for the pre-crisis four quarters are nonsignificant.

[INSERT Table 7.]

Figure 1 presents the point estimates and the 95% confidence intervals of the coefficients on the product of -(*Z-score*) and the measures of lender exposure for the periods before and after the financial crisis. Overall, the results show that the tradeoff between operational hedging spending and the need to avoid financial default is stronger when the firm's ability to raise capital becomes limited. Then, the firm forgoes spending on operational hedging activities and diverts cash to servicing its financial needs, causing its markup to rise.

[INSERT Figure 1.]

3.6 Agency Problems and the Markup–Credit Risk Relationship

We examine an alternative explanation for our results that is based on the agency problem in corporations. Jensen (1986) suggests that debt disciplines managers to be efficient and act in the best interests of shareholders because it forces them to make periodic cash payments in servicing the debt. In the same spirit, Ofek (1993) suggests that, while entrenched management is likely to avoid actions that reduce the firm's costs (e.g., employee layoffs) in crises, financial distress ameliorates this problem by forcing managers to act to avoid default. Ofek finds that, in crises, firms in financial distress are more aggressive in cutting their expenditures.

According to this analysis, financial distress has a stronger effect on cost cutting in firms where managers' interests are not aligned with those of shareholders, that is, in firms with more agency problems. Yet, by our analysis, cutting operational hedging costs and reducing financial distress are consistent with shareholders' interests and should be done by value-maximizing managers.

We test these contrasting explanations by aggregating firms into two groups according to the entrenchment index of Bebchuk, Cohen, and Ferrell (2009), denoted E, which is higher in firms with more takeover-related measures. We rank firms by their E-index for 2006 using data from the Institutional Shareholder Services governance database and consider two groups of firms, those in the top 30% and those in the bottom 30%. We then estimate for each group the effect of the Z-score on markup and the CGS for firms whose lenders were distressed in the 2008 financial crisis, as we do in Table 6. The results are presented in Table A.3, Panel A. We find that for all three measures of lender exposure, the coefficients of -(*Z-score*)×Lender exposure are significantly positive in the markup model and significantly negative for the CGS model only for firms whose E-index is in the bottom 30%. For firms whose E-index is in the top 30%—those considered to have entrenched management—there are no significant effects of -(*Z-score*)$\times$Lender exposure on markup or the CGS.

We repeat this analysis using the more comprehensive measure of the G-index of entrenchment of Gompers, Ishii, and Metrick (2003) for 2006.[21] The estimation results are in Panel B of Table A.3. Here, for both the highest and lowest entrenchment groups, the coefficients of -(*Z-score*)$\times$Lender exposure are significantly positive for the markup model and significantly negative for the CGS model.[22]

[INSERT Table A.3.]

We conclude that the effect of credit risk on markup and the CGS when firms become financially constrained is not explained by the disciplinary effect of debt on entrenched managers. Rather, it is consistent with this relationship reflecting optimal policy by value-maximizing firms that trade off financial resilience with operational resilience.

3.7 Market Power and the Markup-Credit Risk Relationship

We present and test an alternative explanation for the positive markup–credit risk relationship due to Chevalier and Scharfstein (1994) and Gilchrist et al. (2017). We assume that firms are price takers thus changes in their markup reflect changes in marginal cost due to operational hedging. In our model, higher credit risk induces the firm to lower its operational hedging cost, resulting in a wider markup. Chevalier and Scharfstein (1994) and Gilchrist et al.

[21] We appreciate that the authors make the data publicly available on their website.

[22] In untabulated results, we also find that the pre-crisis -(*Z-score*) results are statistically indistinguishable between high and low governance firms, measured by either the E- or the G-index.

(2017) propose that firms with market power that are subject to financial liquidity constraint and higher credit risk may raise their product prices to increase short-term cash flow to alleviate their liquidity needs. The cost of doing that is to forgo the benefits of higher market share and long-run profit. This behavior is worthwhile if the customer base is sticky. According to this analysis, the positive effect of credit risk and financial constraint on markup is stronger for firms with market power. Naturally, the two explanations for the positive markup–credit risk relationship are not mutually exclusive; both motives can play a role: in response to financial distress, firms with market power raise their markup by both raising prices and reducing operation hedging costs, while competitive price-taking firms raise their markup by reducing operational hedging costs alone. The question is whether the positive markup-credit spread relationship, which is stronger when financially constraint is increasing, is present among competitive firms without market power.

We test the effect of market power on the markup-credit risk relationship by re-estimating our markup models separately for firms that rank among the top 5% in their industry in terms of sales and for the remaining firms. The top 5% of firms are viewed as having more market power than the remaining firms, which are more likely to be price takers. We call these two groups HMP and LMP for high and low market power, respectively. The models of Chevalier and Scharfstein (1994) and Gilchrist et al. (2017) explain the positive markup-credit risk relationship for the HMP firms but not for the LMP firms.

We first replicate the test in Table 4 on the effect of -(*Z-score*) on *Markup*. In Table 8, Panel A, we find that for HMP firms, the coefficient of -(*Z-score*) is practically zero, while this coefficient for LMP firms is positive and highly significant. It follows that the positive effect of credit risk on markup is present among LMP firms but not among HMP firms, suggesting that it is not driven by raising product prices.

In Panel B of Table 8, where we replicate the tests of Table 5 for whether markup increases in credit risk during NBER economic recessions, we find that, for HMP firms, credit risk has a positive but nonsignificant effect on the markup during recessions and practically no effect otherwise. For LMP firms, markup always increases as a function of -(*Z-score*), particularly during recessions when firms are subject to financial constraint, as predicted by our second hypothesis.

In Panel C of Table 8, we replicate the analysis of Table 6, testing whether firms with exposure to lenders that were shocked during the 2008 financial crisis were more likely to raise their markup if their financial risk was higher. Specifically, we test the reaction of $Markup$ to the interaction variable -(*Z-score*)×Lender exposure with -(*Z-score*) set at the pre-crisis level for the duration of the crisis. We find that markup increased significantly for LMP firms that were exposed to shocked lenders. There is no significant effect of credit risk and financial constraint on markup for HMP firms .

In conclusion, we find that higher financial risk and financial constraint raise markup significantly for firms with low market power, which are usually price takers and cannot raise their markup by raising prices. By our model, these firms raise their markup by reducing their unit costs through a reduction in operational hedging, which enables them to shift liquid resources to hedge against financial risk. We do not find a significant relationship between credit risk and markup for firms with high market power.

[INSERT Table 8.]

3.8 Product Quality and the Markup–Credit Risk Relationship

Maksimovic and Titman (1991) propose that financial distress reduces firms' incentives to maintain their reputation for supplying high-quality products when quality cannot be observed until after the product is purchased. This is because a reduction in quality can lower costs and increase current cash flows at the expense of bondholders who may receive less in the future. This corporate policy is modeled assuming a finite horizon, which lowers the value of maintaining the long-term reputation of product quality since, in the short term, consumers do not find out about product quality. We suggest that, in the longer term, when consumers find out about the decline in product quality, demand and prices will decline, as will markup.

We test this implication by extending our dynamic analysis in Table 7 by four additional quarters, from two years post-crisis, from 2009 to 2010, to 2011, which is the third year after the crisis. If firms that became financially distressed lowered their product quality by cutting costs and increasing their markup, it would be harder to maintain a lower quality over three years without consumers noticing it. While short-term informational frictions imply that markups can rise when firms cut costs under financial pressure, if many customers discover reduced product quality after roughly three years, prices should decline, reducing markups. Over the long run, it is likely that the lower product quality will lower demand, prices, and markups. Consequently, we expect that the positive effect of the lenders' shock on firms' markups will decline in the third year after the shock compared to its level in the second year.

In Table A.4 of the Appendix, we present estimation results of a model that adds an interaction term for the third year following the crisis to the model in Table 7. This enables us to test whether the coefficient on -(*Z-score*)×*Lender exposure* declines in the longer run, that is, quarters $\{+9, +12\}$, capturing the four quarters in 2011. We find no evidence of that. Across all three measures of lender exposure, the coefficients of -(*Z-score*)×($LE, D_{\{+9,+12\}}$) are not lower than those for -(*Z-score*)×($LE, D_{\{+5,+8\}}$) that pertain to the previous year, and for two measures these coefficients are positive and significant. These results suggest that the increase in markup for firms with higher credit risk whose external financing was shocked reflects managerial optimization through cost reduction on operational hedging rather than a cut in product quality that could be observed over time, leading to delayed reputational correction and lower markup. These findings do not necessarily contradict those of Maksimovic and Titman (1991), since the mechanisms are not mutually exclusive.[23] Rather, our results suggest that the operational hedging channel—whereby firms reduce costly investments in inventory and supply chain diversification to preserve cash for debt service—provides a more complete explanation for the positive relationship between credit risk and markup.

[INSERT Table A.4.]

3.9 Operational Hedging and Value Change during the COVID Pandemic

Our framework suggests that operational hedging is less relevant for firm value when credit risk is high because, for a firm that faces an elevated credit risk, financial default becomes the dominant threat. If the firm defaults on its debt, it might not survive to realize the benefits of its operational hedging. In other words, investments in operational resilience

[23] We thank the editor for pointing this out.

become less valuable when the firm's financial survival is uncertain. This reasoning leads to a testable prediction: the value-enhancing effects of operational hedging are more likely to be present among firms with lower credit risk, while, for firms with high credit risk, operational hedging has little or no effect on firm value since the existential threat of financial default overshadows operational benefits considerations.

We test this prediction indirectly using firms' value change following the COVID shock that created both financial and operational default risks. By our analysis, the level of pre-COVID operational hedging has no beneficial value effect for firms that entered COVID with high pre-existing credit risk but is beneficial for firms with low credit risk. In our test, we estimate a cross-sectional regression of firm stock returns over the years 2020–2021 on our two measures of operational hedging, $Inventory/sales$ ratio and *SCH* (supply chain hedging), both at their level at the end of 2019. The control variables are $Book/market$ ratio and *Size* (in logarithmic form), which are known to affect stock returns across firms, using the end-of-2019 values. The model also includes the percentage change in sales during 2019 to control for mechanical changes of the $Inventory/sales$ ratio in 2019 due to sale changes. We also include industry fixed effects. Finally, we split our sample into two halves by the sample median of -(*Z-score*) and estimate separate regressions for each group.

The estimation results in Table 9 show that firms with lower pre-COVID credit risk benefitted from having higher inventories and greater supply chain diversification before the crisis. For firms with a low -(*Z-score*), the coefficients are positive and significant for both $Inventory/sales$ and *SCH*, implying higher realized returns during the COVID crisis. However, these coefficients are not significantly different from zero for firms with high credit risk, for which operational hedging is less relevant, given the imminent risk of default.

These results are consistent with our theoretical predictions.

[INSERT Table 9.]

4. Conclusion

This paper examines how corporations balance financial efficiency and operational resiliency. We develop a model of a competitive (pricing-taking) firm that must allocate liquidity resources between two forms of hedging: (i) financial hedging through cash reserves to reduce the risk of financial default and (ii) operational hedging through investment in inventory and supply chain network that reduces the risk of operational default such as a failure to deliver on obligations to customers. Our analysis shows that this tradeoff is especially pronounced when the firm faces external financing constraints, leading to a positive relationship between operational spread (markup) and credit risk.

We present empirical evidence supporting our model predictions. We first establish that markup effectively captures a firm's operational hedging activities, as measured by inventory holdings and supply chain hedging. We then demonstrate a robust positive relationship between the firm's markup and its credit risk. This relationship is strengthened when the firm faces heightened incentives to preserve liquidity for averting financial default. Specifically, the markup-credit risk relationship intensifies during economic recessions and became particularly pronounced following the subprime financial crisis, especially for firms whose lenders experienced greater crisis exposure. Overall, our empirical findings strongly support our key premise that the tension between financial and operational hedging becomes more acute when the firm encounters greater external financing constraints.

We conclude by identifying promising directions for future research. From a theoretical perspective, extending our partial equilibrium framework to a general equilibrium production network model would offer valuable insights. In such a model, product pricing, credit risk, and operational hedging decisions would emerge as equilibrium outcomes of the interconnected system, with each firm's operational hedging choices influencing the operational risks faced by its upstream and downstream network partners. This approach would enable an analysis of network externalities in operational hedging, particularly the potential underinvestment in operational resiliency that could arise from credit risk spillovers across connected firms. From an empirical perspective, several important questions await investigation. These include developing a more granular understanding of various operational hedging strategies, evaluating their comparative effectiveness, and precisely measuring their impact on product prices. Addressing these questions will require more comprehensive data on firms' operational hedging practices.

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Figure 1A: Markup–Coefficient on -(*Z-score*)×*Lender exposure*: % # Loans reduction

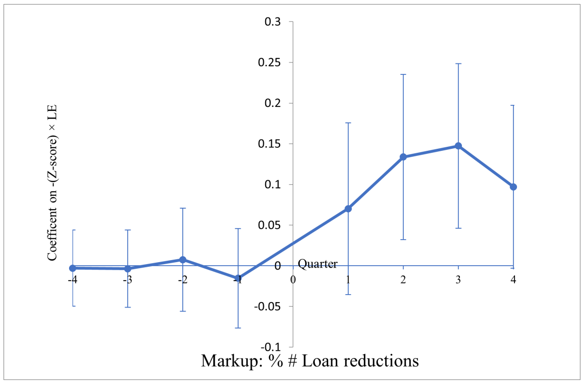

Figure 1B: Markup–Coefficient on -(Z-score)×LE: Lehman exposure

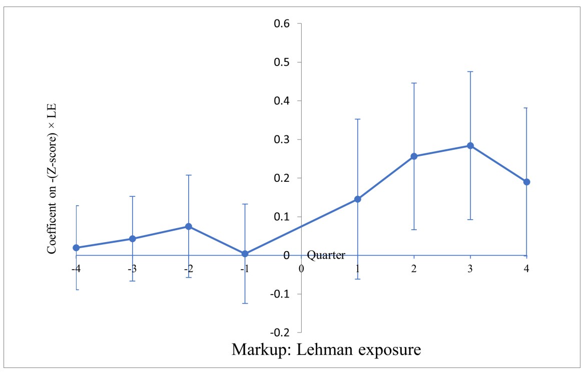

Figure 1C: Markup–Coefficient on -(Z-score)×LE: ABX exposure

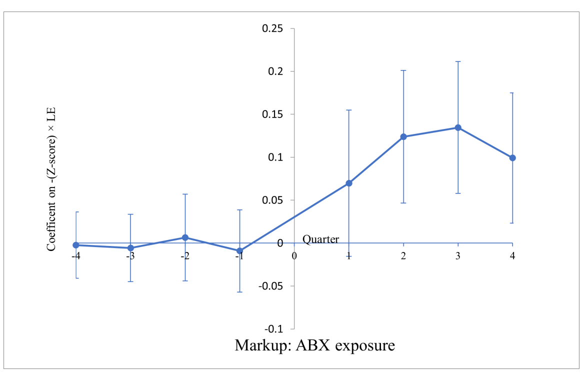

Figure 1D: CGS–Coefficient on -(Z-score)×LE: % # Loans reduction

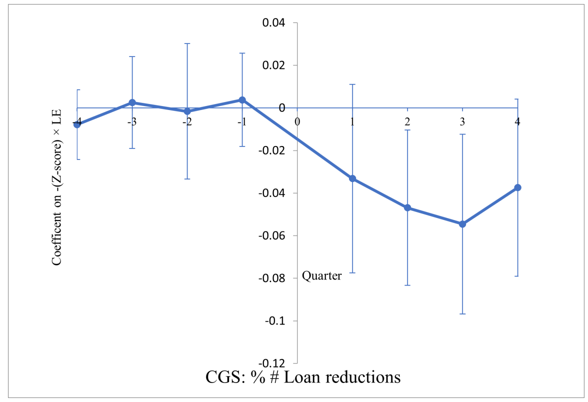

Figure 1E: CGS–Coefficient on -(Z-score)×LE: Lehman exposure

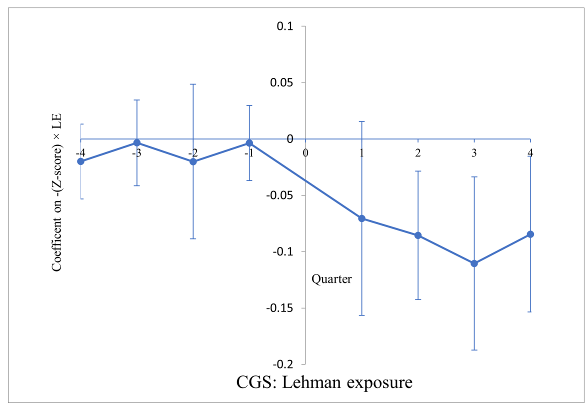

Figure 1F: CGS–Coefficient on -(Z-score)×LE: ABX exposure

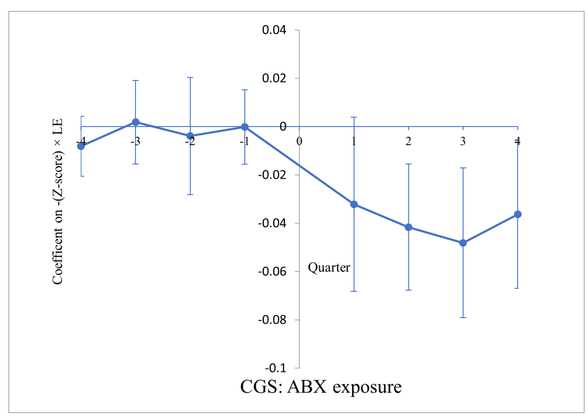

Figure 1: **Markup, CGS and Credit Risk: Dynamic Effects of Exposure to the Financial Crisis**

This figure plots the point estimates of the coefficients on $-(\textit{Z-score}) \times \textit{LE}$ in the markup and CGS regressions, as in Table 7, and their 95% confidence intervals.

Table 1: **Summary Statistics** — Compustat 1973-2020

This table presents summary statistics of the variables in our sample from 1971 to April 2020. The data are quarterly, from Compustat. The variable $Markup$ equals Sales(($SALEQ$) $-$ cost of goods sold($COGSQ$)) / Sales. The variable *CGS/assets* is CGS($COGSQ$)/total assets(ATQ). Z-score, measuring credit risk, is calculated from quarterly data following Altman (1968). Tobin's Q equals the firm's market value (the sum of common shares outstanding($CHOQ$) multiplied by the stock price at the close of the fiscal quarter($PRCCQ$), the preferred stock value($PSTKQ$), dividends on preferred stock($DVPQ$), and liabilities (LTQ)), divided by total assets, following Covas and Den Haan (2011). Cash holdings ($CHEQ$), cash flow ($IBQ + DPQ$) and tangible assets ($PPENTQ$) are scaled by total assets. Market power is measured by two variables, employing Fama and French's 48 industries: a dummy variable that equals one for the top four industry sellers and zero otherwise; and firm's sales/industry sales. The operational hedging variables include inventory–sales ratio ($INVTQ$)/sales (limited to strictly positive values), and supply chain hedging index, denoted SCH, composed from a principal component analysis that employs three measures: (i) ln(1+number of suppliers), (ii) ln(1+number of supplier regions), and (iii) ln(1+number of suppliers not from the firm's region). The variable SCH equals $0.575 \times$ (i) $+ 0.580 \times$ (ii) $+ 0.578 \times$ (iii). Data (sourced from FactSet) are quarterly, covering $6,204$ firms from mid-2003 to the first quarter of 2020. A firm–quarter is included if the lagged firm capitalization is at least \$10 million and quarterly sales are at least \$1 million (inflation adjusted to the end of 2019). All continuous variables are winsorized at both the 1^{st} and 99^{th} percentiles.

VARIABLES	N	Mean	S.D.	P25	P50	P75
$Markup$: (sales-cogs)/sales	572,345	0.317	0.428	0.208	0.338	0.508
CGS/assets	569,049	0.209	0.188	0.079	0.162	0.277
-(Z-score)	573,041	-3.542	5.872	-3.995	-2.082	-1.081
Tobin's Q	573,041	1.981	1.597	1.073	1.446	2.211
Cash holdings	573,041	0.164	0.197	0.024	0.082	0.232
Cash flow	573,041	0.010	0.056	0.005	0.021	0.035
Asset tangibility	573,041	0.303	0.243	0.104	0.235	0.448
Top 4 industry seller	573,041	0.039	0.193	0.000	0.000	0.000
Sales/industry sales	573,041	0.009	0.026	0.000	0.001	0.005
Total assets	573,041	2,738.859	8,390.609	79.178	299.321	1,338.695
Inventory/sales	465,600	0.592	0.520	0.224	0.489	0.793
Supply chain hedging (SCH)	116,430	-0.010	1.697	-1.334	-0.381	0.956

Table 2: **The Effect of Operational Hedging on Changes in Sales during NBER Recessions**

This table presents the results of cross-sectional regressions of changes of firms' sales–assets ratio during recessions on their operational hedging variables, $Inventory/sales$ and SCH. The dependent variable is $\Delta(Sales/assets)$, the difference between average $Sales/assets$ during the recession quarters and average $Sales/assets$ over eight quarters before the recession. The recession quarters are as designated by the NBER. The $Inventory/sales$ and SCH are defined in Table 1; their value is fixed at four quarters before the recession onset (or earlier). All regressions include control variables: Tobin's Q, total assets in logarithmic form, cash holdings, cash flow, and asset tangibility. All the control variables are fixed as of the last quarter before the onset of each recession. The table presents the cross-sectional coefficients for each NBER recession. We include Fama-French 48 industry fixed effects, with standard errors (in parentheses) clustered at the industry level. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	Δ *Sales/assets*					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Inventory–sales ratio						
Recession period	1973Q4 — 1975Q1	1979Q2 — 1980Q2	1981Q2 — 1982Q2	1989Q4 — 1991Q1	2001Q1 — 2001Q3	2007Q4 — 2009Q2
Inventory/sales	0.037**	0.016**	0.013*	0.016***	0.021***	0.011**
Standard error	0.015	0.008	0.007	0.004	0.004	0.005

Panel B: Supply chain hedging principal component analysis, for the recession of 2007Q4 to 2009Q2	
	SCH
SCH	0.002**
Standard error	0.001
Control variables	Yes
Fama-French 48 industry fixed effects	Yes

Table 3: **Markup, CGS and Operational Hedging**

This table presents the estimation of the effect on *Markup* (columns 1 and 2), *CGS/assets* (columns 3 and 4) of two operational hedging measures: SCH, the first principal component of three supply chain diversification measures, and the inventory–sales ratio. The control variables include Tobin's Q, total assets in logarithmic form, cash holdings, cash flow, tangible assets, and two market power variables (in the even-numbered columns). All explanatory variables are lagged by one quarter. The CGS regressions (columns 3 and 4) also include contemporaneous sales–assets ratio. The variable definitions are in Table 1. The regressions include firm and Fama-French 48 industry×year–quarter fixed effects. Standard errors in parentheses are clustered at the firm and year–quarter levels. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*		*CGS/assets*	
	(1)	(2)	(3)	(4)
SCH	-0.0076***	-0.0042**	0.00088***	0.00063**
	(0.0021)	(0.0018)	(0.00030)	(0.00029)
Inventory/sales	-0.076***	-0.076***	0.0061***	0.0067***
	(0.014)	(0.014)	(0.0013)	(0.0013)
Market power variables	No	Yes	No	Yes
Other Control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry×year–quarter fixed effects	No	Yes	No	Yes
Observations	93,853	92,762	93,772	92,681
R-Squared	0.698	0.718	0.975	0.977

Table 4: **Markup, CGS and Credit Risk**

This table presents the results of regressions of *Markup* and *CGS/assets* on credit risk, measured by Altman's (1968) -(*Z-score*). The dependent variables are the quarterly *Markup* (columns 1 and 2) and *CGS/assets* (columns 3 and 4). The control variables include Tobin's Q, total assets in logarithmic form, cash holdings, cash flow, tangible assets, and two market power variables (in the even-numbered columns). All control variables are lagged by one quarter. The CGS models also include contemporaneous $Sales/assets$. The variable definitions are in Table 1. The regressions include firm and Fama-French 48 industry×year–quarter fixed effects. Standard errors (in parentheses) are clustered at the firm and year–quarter levels. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*		*CGS/assets*	
	(1)	(2)	(3)	(4)
-(Z-score)	0.0037***	0.0029***	-0.00058***	-0.00054***
	(0.00057)	(0.00053)	(0.000080)	(0.000079)
Market power variables	No	Yes	No	Yes
Other control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry×year–quarter fixed effects	No	Yes	No	Yes
Observations	571,388	564,418	568,015	561,177
R-Squared	0.614	0.634	0.949	0.951

Table 5: **Markup, CGS and Credit Risk: NBER Recessions**

This table presents the results of regressions of *Markup* or *CGS/assets* on -(*Z-score*) that interacts with a recession dummy variable (*Recession*) equal to one for the following quarters: 1973Q4–1975Q1, 1979Q2–1980Q2, 1981Q2–1982Q2, 1989Q4–1991Q1, 2001Q1–2001Q3, and 2007Q4–2009Q2. (The COVID-related recession in 2020Q1 is excluded.) For each recession, the values of -(*Z-score*) and the control variables for the duration of the recession are fixed as of the last quarter before the onset of the recession. The control variables are as in Table 4. The regressions include firm and Fama-French 48 industry×year-quarter fixed effects. Standard errors (in parentheses) are clustered at the firm and year–quarter levels. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

VARIABLES	*Markup*		*CGS/assets*	
	(1)	(2)	(3)	(4)
-(Z-score)×Recession	0.0019**	0.0016***	-0.00023**	-0.00025**
	(0.00075)	(0.00051)	(0.00011)	(0.00010)
-(Z-score)	0.0035***	0.0028***	-0.00057***	-0.00053***
	(0.00056)	(0.00052)	(0.000077)	(0.000077)
Market power variables	No	Yes	No	Yes
Other control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry×Year-quarter fixed effects	No	Yes	No	Yes
Observations	563,120	554,348	560,343	551,691
R-Squared	0.616	0.636	0.948	0.950

Table 6: **Markup, CGS, Inventory, SCH and Credit risk: Exposure to the Financial Crisis**

This table presents the results of regressions of *Markup* and *CGS/assets* in Panel A, *Inventory/sales* ($INVT$) and supply chain hedging (SCH) in Panel B, and *Net leverage* in Panel C, defined as the ratio of financial debt ($DLTTQ$ plus $DLCQ$) minus cash ($CHEQ$) scaled by total assets. The estimated model is (3.3). The main explanatory variable is the firm's -(*Z-score*) that interacts with the extent of the firm's lender exposure to the 2008 financial crisis. The sample include the 2,429 firms of Chodorow-Reich (2014). The estimation is over two-year periods before and after the crisis, from January 2006 to December 2007 and from January 2009 to December 2010, respectively. The three measures for crisis exposure are the percentage of loans reduction, Lehman exposure, and ABX exposure, using Chodorow-Reich's (2014) variables. The lender exposure variables equal zero for the two-year period before the crisis and equal their actual value for the two-year period after the crisis. The values of *-(Z-score)* are as of the end of 2007. The firm-level control variables (including market power variables) are as in Table 4, fixed at the end of 2007 for the post-crisis period. The CGS regressions include the contemporaneous $Sales/assets$. The regressions include the interaction terms of the control variables×lender exposure. Firm and Fama-French 48 industry×year–quarter fixed effects. Standard errors (in parentheses) are clustered by firm. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

Panel A: Markup, CGS and Credit Risk: Exposure to the Financial Crisis

	% # Loans reduction		Lehman exposure		ABX exposure	
VARIABLES	*Markup*	*CGS/assets*	*Markup*	*CGS/assets*	*Markup*	*CGS/assets*
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score)×lender exposure	0.108**	-0.034**	0.188**	-0.064***	0.104***	-0.031***
	(0.044)	(0.014)	(0.089)	(0.023)	(0.034)	(0.010)
Lender exposure	-0.778	-0.005	-0.833	-0.248	-0.884*	-0.038
	(0.529)	(0.196)	(0.770)	(0.246)	(0.453)	(0.147)
Market power variables				Yes		
Market power variables×lender exposure				Yes		
Other control variables				Yes		
Other control variables×lender exposure				Yes		
Firm fixed effects				Yes		
Industry×year–quarter fixed effects				Yes		
Observations	20,333	20,328	20,333	20,328	20,333	20,328
R-Squared	0.901	0.986	0.901	0.986	0.901	0.986

Panel B: Inventory, SCH and credit risk: Exposure to the financial crisis

	% # Loans reduction		Lehman exposure		ABX exposure	
VARIABLES	*INVT*	*SCH*	*INVT*	*SCH*	*INVT*	*SCH*
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score)×lender exposure	-0.168**	-0.260	-0.291*	-0.896	-0.132**	-0.551**
	(0.078)	(0.338)	(0.177)	(0.781)	(0.066)	(0.280)
Lender exposure	1.499	-0.592	0.782	13.449	1.133	11.346**
	(1.136)	(6.226)	(2.187)	(11.093)	(1.063)	(5.431)
Market power variables			Yes			
Market power variables×lender exposure			Yes			
Other control variables			Yes			
Other control variables×lender exposure			Yes			
Firm fixed effects			Yes			
Industry×Year–quarter fixed effects			Yes			
Observations	19,959	13,423	19,959	13,423	19,959	13,423
R-Squared	0.881	0.929	0.881	0.929	0.881	0.929

Panel C: Net Leverage and Credit Risk: Exposure to the Financial Crisis

	% # Loans reduction	Lehman exposure	ABX exposure
VARIABLES		*Net leverage*	
	(1)	(2)	(3)
-(Z-score)×lender exposure	-0.275***	-0.663***	-0.205***
	(0.098)	(0.192)	(0.079)
Lender exposure	-0.148	-0.396	-0.594
	(0.938)	(1.733)	(0.907)
Market power variables		Yes	
Market power variables×lender exposure		Yes	
Other control variables		Yes	
Other control variables×lender exposure		Yes	
Firm fixed effects		Yes	
Industry×year–quarter fixed effects		Yes	
Observations	19,901	19,901	19,901
R-Squared	0.892	0.892	0.892

Table 7: **Dynamic Effects of Exposure to the Financial Crisis for Markup, CGS and Credit Risk**

This table presents the results of regressions of *Markup* and *CGS/sales* on the firm's -(*Z-score*) that interacts with the extent of lender exposure to the 2008 financial crisis. The estimation model is (3.3), replacing the lender exposure variable with (LE, D_n), which is the actual value of lender exposure, measured by three variables from Chodorow-Reich (2014) (see Table 6) for quarter n and zero otherwise, where n equals $-1, -2, -3, -4, +1, +2, +3, +4, \{+5, +8\}$, with $\{+5, +8\}$ capturing quarters +5 to +8. This numbering pertains to the last four quarters in the pre-crisis period, Q1–Q4/2007; the four post-crisis quarters, Q1–Q4/2009; and $D_{\{+5,+8\}} = 1$ for the quarters Q1–Q4/2010. The values of -(*Z-score*) are as of the end of 2007. The firm-level control variables are as in Table 4, fixed at the end of 2007 for the entire post-crisis period. The last two rows show the results from F-tests for the joint significance of the coefficients of the interaction terms between -(*Z-score*) and (LE, D_n). The regressions include firm and Fama-French 48 industry×year–quarter fixed effects. Standard errors (in parentheses) are clustered by firm. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

	% # Loans reduction		Lehman exposure		ABX exposure	
VARIABLES	*Markup*	*CGS/assets*	*Markup*	*CGS/assets*	*Markup*	*CGS/assets*
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score) × LE, D_{-4}	-0.003	-0.008	0.020	-0.020	-0.002	-0.008
	(0.024)	(0.008)	(0.055)	(0.017)	(0.020)	(0.006)
-(Z-score) × LE, D_{-3}	-0.004	0.002	0.043	-0.004	-0.006	0.002
	(0.024)	(0.011)	(0.056)	(0.019)	(0.020)	(0.009)
-(Z-score) × LE, D_{-2}	0.008	-0.002	0.075	-0.020	0.006	-0.004
	(0.032)	(0.016)	(0.067)	(0.035)	(0.026)	(0.012)
-(Z-score) × LE, D_{-1}	-0.015	0.004	0.004	-0.004	-0.009	-0.000
	(0.031)	(0.011)	(0.066)	(0.017)	(0.024)	(0.008)
-(Z-score) × LE, D_1	0.070	-0.033	0.145	-0.071	0.070	-0.032*
	(0.054)	(0.023)	(0.106)	(0.044)	(0.043)	(0.018)
-(Z-score) × LE, D_2	0.134***	-0.047**	0.256***	-0.086***	0.124***	-0.042***
	(0.052)	(0.019)	(0.097)	(0.029)	(0.039)	(0.013)
-(Z-score) × LE, D_3	0.147***	-0.055**	0.284***	-0.111***	0.135***	-0.048***
	(0.052)	(0.022)	(0.098)	(0.039)	(0.039)	(0.016)
-(Z-score) × LE, D_4	0.097*	-0.037*	0.190*	-0.085**	0.099**	-0.036**
	(0.051)	(0.021)	(0.097)	(0.035)	(0.039)	(0.016)
-(Z-score) × LE, $D_{\{+5,+8\}}$	0.096*	-0.024	0.184*	-0.049*	0.095**	-0.024**
	(0.050)	(0.016)	(0.104)	(0.026)	(0.040)	(0.012)
Lender exposure, D_n				Yes		
Control variables				Yes		
Control variables×Lender exposure				Yes		
Firm fixed effects				Yes		
Industry×year–quarter fixed effects				Yes		
Observations	19,596	19,591	19,596	19,591	19,596	19,591
R-Squared	0.899	0.986	0.899	0.986	0.899	0.986
F-Statistic for $n = +1$ to $+4$	3.36***	2.32**	3.27**	2.71**	3.79***	2.83**
F-Statistic for $n = -1$ to -4	0.27	0.59	0.41	0.41	0.27	0.67

Table 8: **Markup and Credit Risk: Separate Estimations by Market Power**

Panel A replicates the test of Table 4: regressions of *Markup* on -(*Z-score*). Panel B replicates the test inTable 5: regressions of *Markup* on -(*Z-score*) that interacts with indicators of NBER recession periods. Panel C replicates the tests in Table 6: regressions of *Markup* on -(*Z-score*) that interacts with the exposures to the 2008 Financial Crisis. Firms are sorted in each quarter into two groups by their sales scaled by total industry sales: Those with high market power (HMP) rank among the top 5% in the industry; the remaining firms have low market power (LMP). We estimate our models separately for each group based on sorting in the lagged quarter. All models include control variables and firm and industry×year–quarter fixed effects. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

	Panel A: Baseline		Panel B: NBER Recessions	
	HMP	LMP	HMP	LMP
VARIABLES		Markup		
	(1)	(2)	(3)	(4)
-(Z-score)	0.00013	0.0029***	-0.00030	0.0028***
	(0.0015)	(0.00053)	(0.0015)	(0.00052)
-(Z-score)×Recession			0.0024	0.0016***
			(0.0018)	(0.00051)
Control variables			Yes	
Firm fixed effects			Yes	
Industry×year–quarter fixed effects			Yes	
Observations	23,681	539,460	23,282	529,811
R-Squared	0.903	0.633	0.901	0.635

Panel C: 2008 Financial Crisis

	% # Loans reduction		Lehman exposure		ABX exposure	
	HMP	LMP	HMP	LMP	HMP	LMP
VARIABLES			*Markup*			
	(1)	(2)	(3)	(4)	(5)	(6)
-(Z-score)×lender exposure	0.132	0.109**	0.548	0.193**	0.221	0.105***
	(0.203)	(0.044)	(0.374)	(0.090)	(0.230)	(0.034)
Lender exposure	3.397	-0.742	2.096	-0.831	1.939	-0.868*
	(2.660)	(0.590)	(4.022)	(0.859)	(2.424)	(0.496)
Control variables			Yes			
Firm fixed effects			Yes			
Industry×year–quarter fixed effects			Yes			
Observations	826	19,318	826	19,318	826	19,318
R-Squared	0.981	0.898	0.981	0.898	0.981	0.899

Table 9: **Operational Hedging and Stock Return during COVID Period**

This table presents the results of cross-sectional regressions of firms' cumulative stock returns over the two-year period 2020–2021 on measures of operational hedging at the end of 2019, namely, SCH, which measures supply chain diversification, and the inventory–sales ratio, both defined in Table 1. The control variables are $Book/market$ ratio and equity capitalization (both in logarithmic form), denoted $ln(B/M)$ and $ln(Size)$, and the percentage changes in sales in 2019. The regressions include Fama-French 48 industry fixed effects. High and low -(*Z-score*) values are defined as -(*Z-score*) being above and below the end-of-2019 sample median, respectively. Standard errors are clustered by Fama-French 48 industry. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

	2020 — 2021 stock return		
	Full sample	High -(Z-score)	Low -(Z-score)
	(1)	(2)	(3)
Ln(inventory/sales)	0.015	-0.020	0.051*
	(0.030)	(0.054)	(0.029)
SCH	0.064***	0.021	0.049**
	(0.023)	(0.035)	(0.022)
Ln(B/M)	-0.227***	-0.161	-0.296***
	(0.075)	(0.184)	(0.074)
Ln(size)	-0.135***	-0.171***	-0.052*
	(0.034)	(0.057)	(0.026)
% changes in sales, 2019	-0.190	-0.359	0.132
	(0.218)	(0.354)	(0.254)
Industry fixed effects		Yes	
Observations	1,664	795	737
R-Squared	0.070	0.096	0.161

Appendix

Table A.1: **Markup, CGS and Credit Risk—Complete Table**

This table reports all the coefficients estimated in Table 4.

VARIABLES	*Markup*		*CGS/assets*	
	(1)	(2)	(3)	(4)
-(Z-score)	0.0037***	0.0029***	-0.00058***	-0.00054***
	(0.00057)	(0.00053)	(0.000080)	(0.000079)
Tobin's Q	0.021***	0.019***	-0.0048***	-0.0048***
	(0.0020)	(0.0019)	(0.00036)	(0.00035)
Ln assets	0.0073***	0.0058**	0.0035***	0.0036***
	(0.0028)	(0.0026)	(0.00049)	(0.00054)
Cash holdings	-0.070***	-0.065***	0.0010	0.0012
	(0.015)	(0.015)	(0.0022)	(0.0022)
Cash flow	0.91***	0.85***	-0.19***	-0.18***
	(0.044)	(0.038)	(0.0072)	(0.0069)
Asset tangibility	-0.035**	-0.0061	-0.015***	-0.015***
	(0.014)	(0.014)	(0.0029)	(0.0029)
Top 4 industry seller		-0.00019		0.00018
		(0.0047)		(0.0019)
Sales/industry sales		-0.28***		0.071***
		(0.078)		(0.021)
Sales/AT			0.75***	0.75***
			(0.0054)	(0.0054)
Market power variables	No	Yes	No	Yes
Other control variables	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Industry×Year–quarter fixed effects	No	Yes	No	Yes
Observations	571,388	564,418	568,015	561,177
R-Squared	0.614	0.634	0.949	0.951

Table A.2: **Pre-Crisis Firm Characteristics by Crisis Exposure Level**

This table presents the results of firm characteristics before the financial crisis across exposure quartiles (Q1–Q4), measured at the end of 2007. Firms are sorted into quartiles based on three different measures of exposure to the 2008 financial crisis: the percentage of loan reduction, Lehman exposure, and ABX exposure, as defined in Table 6, with exposure increasing from Q1 to Q4 (from lowest to highest exposure). The table reports the mean values for each quartile and the difference between the means of Q1 and Q4, with the corresponding t-statistic in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively. The means are presented for each quartile in three rows corresponding to the three measures of exposure to the 2008 financial crisis, in the following order: the percentage of loan reduction, Lehman exposure and ABX exposure.

	Exposure measures	Q1	Q2	Q3	Q4	Difference Q1-Q4
-(Z-score)	%ΔLoan	-3.121	-2.967	-2.684	-2.220	-0.902*** (-4.162)
	Lehman	-3.339	-3.024	-2.479	-2.047	-1.292*** (-5.948)
	ABX	-2.838	-2.948	-2.782	-2.434	-0.404 (-1.812)
Tobin's Q	%ΔLoan	1.912	1.769	1.894	1.807	0.105 (1.376)
	Lehman	1.991	1.805	1.772	1.810	0.181* (2.239)
	ABX	1.878	1.812	1.821	1.869	0.009 (0.111)
Asset tangibility	%ΔLoan	0.303	0.283	0.289	0.279	0.024 (1.287)
	Lehman	0.240	0.288	0.304	0.324	-0.083*** (-4.826)
	ABX	0.268	0.295	0.295	0.296	-0.028 (-1.552)
Ln assets	%ΔLoan	6.499	7.298	7.965	7.270	-0.772*** (-6.865)
	Lehman	6.401	7.240	7.659	7.793	-1.392*** (-12.482)
	ABX	6.414	7.175	7.747	7.729	-1.315*** (-11.234)
Cash holdings	%ΔLoan	0.111	0.098	0.094	0.102	0.009 (0.972)
	Lehman	0.134	0.094	0.080	0.095	0.039*** (3.951)
	ABX	0.123	0.105	0.086	0.090	0.033*** (3.544)
Cash flow	%ΔLoan	0.022	0.019	0.020	0.021	0.001 (0.617)
	Lehman	0.021	0.021	0.021	0.019	0.002 (0.659)
	ABX	0.016	0.020	0.022	0.023	-0.007** (-2.610)
Sales/industry sales	%ΔLoan	0.005	0.015	0.022	0.016	-0.011*** (-5.515)
	Lehman	0.006	0.014	0.016	0.022	-0.016*** (-7.115)
	ABX	0.008	0.014	0.017	0.019	-0.012*** (-5.292)
Top 4 industry sellers	%ΔLoan	0.022	0.052	0.097	0.074	-0.052** (-3.243)
	Lehman	0.020	0.056	0.071	0.101	-0.082*** (-4.635)
	ABX	0.033	0.055	0.069	0.090	-0.057** (-3.220)

Table A.3: **Corporate Governance and the Credit Risk Effect on Markup and CGS: Exposure to the Financial Crisis**

This table presents the results of regressions of *Markup* and *CGS/assets* on the firm's -(*Z-score*) that interacts with the extent of exposure to the 2008 financial crisis for firms grouped by corporate governance index levels. The table replicates the analysis in Table 6 for firms grouped by their entrenchment E-index following Bebchuk, Cohen, and Ferrell (2009) (Panel A) and G-index following Gompers, Ishii, and Metrick (2003) (Panel B) using end-of-2006 values. Firms are classified into high- and low-E groups and high- and low-G groups by whether the values of their E- or G-index is among the top or bottom 30% of firms, respectively. Other specifications are the same as in Table 6. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Top 30% vs. Bottom 30% E-index

	% # Loans reduction				Lehman exposure				ABX exposure			
VARIABLES	*Markup*		*CGS/assets*		*Markup*		*CGS/assets*		*Markup*		*CGS/assets*	
	High E	Low E	High E	Low E	High E	Low E	High E	Low E	High E	Low E	High E	Low E
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
-(Z-score)×lender exposure	-0.031	0.376***	0.048	-0.100***	-0.158	0.687***	0.125	-0.176***	0.013	0.358***	0.023	-0.094***
	(0.143)	(0.106)	(0.046)	(0.029)	(0.225)	(0.187)	(0.087)	(0.058)	(0.093)	(0.090)	(0.028)	(0.027)
Lender exposure	2.902	0.551	-1.230*	-0.162	3.105	-0.325	-1.615	-1.246*	-0.599	-0.872	-0.232	-0.210
	(3.006)	(2.520)	(0.672)	(0.549)	(4.254)	(2.721)	(1.104)	(0.723)	(1.853)	(2.534)	(0.453)	(0.552)
Market power variables							Yes					
Market power variables×lender exposure							Yes					
Other control variables							Yes					
Other control variables×lender exposure							Yes					
Firm fixed effects							Yes					
Industry×year–quarter fixed effects							Yes					
Observations	2,443	2,365	2,442	2,365	2,443	2,365	2,442	2,365	2,443	2,365	2,442	2,365
R-squared	0.946	0.960	0.993	0.993	0.946	0.958	0.993	0.993	0.947	0.960	0.993	0.993

Panel B: Top 30% vs. Bottom 30% of G-Index

	% # Loans reduction				Lehman exposure				ABX exposure			
VARIABLES	*Markup*		*CGS/assets*		*Markup*		*CGS/assets*		*Markup*		*CGS/assets*	
	High G	Low G	High G	Low G	High G	Low G	High G	Low G	High G	Low G	High G	Low G
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
-(Z-score)×lender exposure	0.318***	0.303***	-0.052**	-0.082***	0.670**	0.931***	-0.115**	-0.239***	0.262**	0.284***	-0.044**	-0.075***
	(0.112)	(0.100)	(0.025)	(0.021)	(0.258)	(0.301)	(0.054)	(0.057)	(0.101)	(0.086)	(0.022)	(0.018)
Lender exposure	2.553	-1.776	-1.103*	0.342	4.740	-1.178	-1.338	-0.971	1.287	-0.618	-0.820*	-0.011
	(1.778)	(2.655)	(0.662)	(0.533)	(2.940)	(3.275)	(0.979)	(0.762)	(1.457)	(2.633)	(0.462)	(0.569)
Market power variables							Yes					
Market power variables×lender exposure							Yes					
Other control variables							Yes					
Other control variables×lender exposure							Yes					
Firm fixed effects							Yes					
Industry×year-quarter fixed effects							Yes					
Observations	2,137	2,701	2,137	2,700	2,137	2,701	2,137	2,700	2,137	2,701	2,137	2,700
R-squared	0.965	0.928	0.996	0.992	0.965	0.927	0.996	0.992	0.965	0.928	0.996	0.992

Table A.4: **Dynamic Effects of Exposure to the Financial Crisis on the Markup–Credit Risk Relationship up to Three Years after the Crisis**

This table presents the results of regressions of *Markup* on the firm's -(*Z-score*) that interacts with the extent of lender exposure to the 2008 Financial Crisis. The specification of this table is the same as in Table 7 except that we extend the post-crisis period to include Q1–Q4/2011, represented by the dummy variable $D_{\{+9,+12\}}$. The periods before and after the crisis are January 2006 to December 2007 and January 2009 to December 2011, respectively. The term D_n now includes $n = -1, -2, -3, -4, +1, +2, +3, +4, \{+5, +8\}, \{+9, +12\}$, where $D_{\{+n_1,+n_2\}}$ captures quarters n_1 to n_2 after the end of 2008. The last two rows show the results from F-tests for joint significance of the coefficients of the interaction terms between -(*Z-score*) and (LE, D_n). The regressions include firm and Fama-French 48 industry×year–quarter fixed effects. Standard errors are clustered by firm. $*$, $**$, and $***$ denote significance below the 10%, 5%, and 1% levels, respectively.

	% # Loans reduction	Lehman exposure	ABX exposure
VARIABLES	*Markup*	*Markup*	*Markup*
	(1)	(2)	(3)
-(Z-score) × LE, D_{-4}	-0.005	0.017	-0.004
	(0.024)	(0.055)	(0.019)
-(Z-score) × LE, D_{-3}	-0.007	0.036	-0.008
	(0.024)	(0.055)	(0.020)
-(Z-score) × LE, D_{-2}	0.005	0.070	0.004
	(0.032)	(0.067)	(0.025)
-(Z-score) × LE, D_{-1}	-0.019	-0.004	-0.012
	(0.031)	(0.064)	(0.024)
-(Z-score) × LE, D_1	0.060	0.122	0.062
	(0.052)	(0.103)	(0.042)
-(Z-score) × LE, D_2	0.122**	0.227**	0.114***
	(0.051)	(0.096)	(0.038)
-(Z-score) × LE, D_3	0.136***	0.255***	0.125***
	(0.050)	(0.097)	(0.038)
-(Z-score) × LE, D_4	0.085*	0.162*	0.089**
	(0.050)	(0.097)	(0.038)
-(Z-score) × LE, $D_{\{+5,+8\}}$	0.082	0.153	0.084**
	(0.051)	(0.107)	(0.040)
-(Z-score) × LE, $D_{\{+9,+12\}}$	0.109*	0.183	0.102**
	(0.059)	(0.135)	(0.047)
Lender exposure, D_n		Yes	
Control variables		Yes	
Control variables×Lender exposure		Yes	
Firm fixed effects		Yes	
Industry×year-quarter fixed effects		Yes	
Observations	24,138	24,138	24,138
R-Squared	0.901	0.901	0.902
F-Statistic for $n = +1$ to $+4$	3.24**	2.93**	3.59***
F-Statistic for $n = -1$ to -4	0.34	0.41	0.32